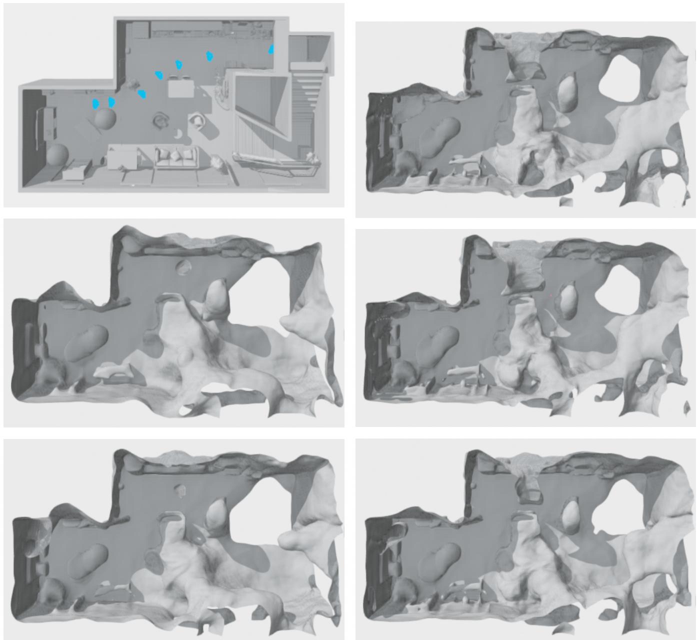
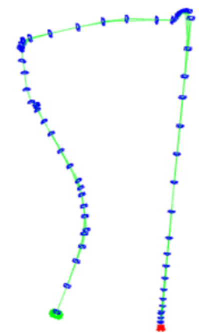


Fig. 9. Progression of non-incrementally trained mesh: ground truth (top left), 200, 500, 1000, and 2000 steps clockwise.

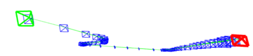
varying heights within the room. Additionally, examples of the mesh object generated by the SDF are presented in Figure 11 and Figure 12. Although no ground truth mesh was available for the dataset collected, we qualitatively assess our results as reasonably accurate based on our observations of the mesh and the PROGRESS Lab. For instance, Figure 12 shows a precise depiction of the filing cabinets along the right side of the room and the desk and chair on the top left.

V. Conclusions

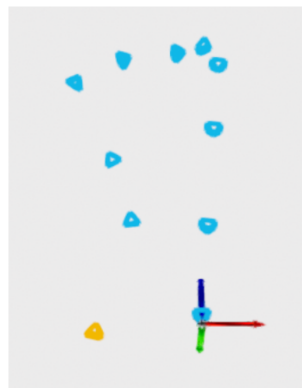
In this study, we explored the performance of the incremental signed distance field (iSDF) neural network for reconstructing environments from RGB-D images and pose information. We conducted three experiments to evaluate the capabilities of the iSDF network. The first experiment was to train the network incrementally on the *apt_2_nav* dataset, which demonstrated that the network could learn the environment over time with improving accuracy of the generated SDF. The second experiment trained the network non-incrementally on all nine keyframes from the same dataset, and achieved an SDF error of 14cm and a collision cost error of 0.12. Although these results were worse than those reported in the original paper, they were within an order of magnitude and could be explained by computational limitations. Finally, we conducted a real-world experiment in the PROGRESS Lab to evaluate the feasibility of extending iSDF to new environments. Although we could not evaluate the accuracy of our results quantitatively, our observations of the generated SDF and the mesh object led us to conclude that the iSDF network can sufficiently reconstruct complex environments.



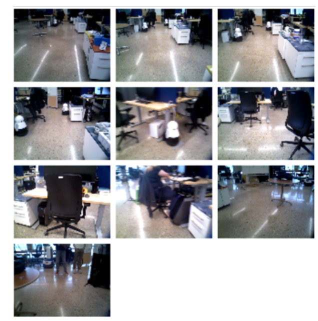
(a)



(b)



(c)



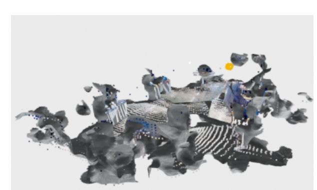
(d)

Fig. 10. Overview of robot trajectory showing (a) a top-down view of ORB-SLAM3 estimated trajectory, (b) a standing/level-view of the ORB-SLAM3 estimated trajectory, (c) locations of keyframes used by iSDF and (d) the keyframes used.

(a)

(b)

(c)



(d)

Fig. 11. Alternative perspectives on mesh from the FRB 2150's side south entrance (a,b) and north entrance (c,d) with visuals of the measured depth point cloud (DPC) (a,c) and DPC overlayed on the generated mesh (b,d).

Fig. 12. Generated Mesh of PROGRESS Lab

Overall, our findings show that iSDF is a promising method of generating accurate reconstruction of complex environments. Future research could include the addition of semantic labeling to the mesh generation and the expansion into outdoor environments and those larger than room-scale.

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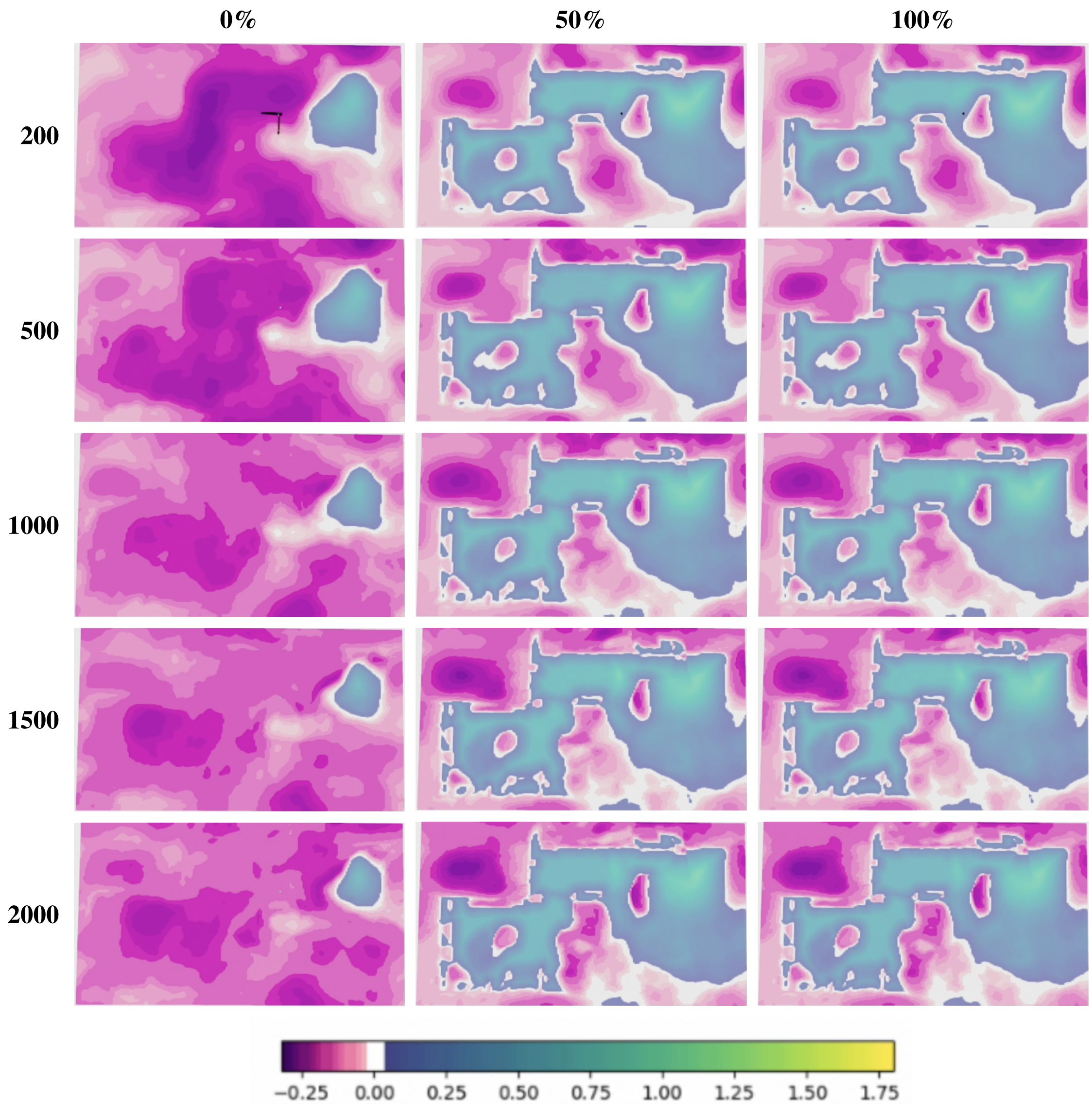

Fig. 13. Progress of SDF in non-incremental experiment with number of training steps on the y-axis and slice height percentage (0% = bottom of environment, 100% = top of environment) on the x-axis.